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Research Paper

Interoperability Challenges in Electronic Health Record Systems with Emphasis on HL7 FHIR Adoption and Data Standardization

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Abstract: Interoperability of Electronic Health Record (EHR) systems remains a persistent challenge despite widespread digitization and the growing adoption of standardized exchange frameworks. In recent years, HL7 Fast Healthcare Interoperability Resources (FHIR) has emerged as a dominant standard intended to facilitate seamless health information exchange across healthcare organizations. However, real-world implementations continue to exhibit limitations related to data completeness, semantic consistency, and cross-hospital exchange reliability. This study presents a quantitative, data-driven analysis of EHR interoperability challenges by examining FHIR-compliant synthetic datasets representing multiple healthcare organizations. Using a Python-based analytical pipeline, the study evaluates structural interoperability, semantic conformity, and exchange performance through formally defined metrics and statistical analysis. The results reveal significant variability across organizations and resource types, demonstrating that technical standard adoption alone does not ensure meaningful interoperability. The findings provide empirical evidence to inform healthcare organizations, vendors, and policymakers on critical gaps in current interoperability practices and offer insights for improving standardized EHR data exchange.

Keywords: Electronic Health Records; Interoperability; HL7 FHIR; Health Information Exchange; Data Standardization; Healthcare IT

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1. Introduction

The digitization of healthcare information through Electronic Health Record systems has fundamentally transformed clinical documentation, data storage, and care coordination. Despite near-universal EHR adoption in many healthcare systems, the ability to exchange health information seamlessly across organizational boundaries remains limited. Interoperability challenges hinder continuity of care, contribute to clinician burden, and reduce the potential value of health data for analytics and decision support. To address these challenges, standards-based approaches—most notably HL7 Fast Healthcare Interoperability Resources—have been promoted as a foundation for modern health information exchange. FHIR introduces a resource-oriented, API-driven framework designed to improve accessibility, scalability, and developer adoption compared to earlier interoperability standards [1-5]. Experience from real-world deployments indicates that FHIR adoption alone does not guarantee interoperable outcomes. Variations in implementation practices, inconsistent data modeling, partial resource population, and heterogeneous terminology usage continue to limit semantic and operational interoperability. As healthcare delivery increasingly relies on cross-institutional care models, telehealth, and patient-mediated data sharing, the need for empirically grounded evaluations of interoperability performance has become more pressing [6-10]. This paper addresses this need by presenting a quantitative analysis of interoperability challenges in EHR systems using FHIR-compliant data. The remainder of the paper is organized as follows: Section 2 reviews related literature on EHR interoperability and FHIR adoption; Section 3 describes the data-driven methodology employed in this study; Section 4 presents the empirical results; Section 5 discusses the implications of the findings; and Section 6 concludes the paper with recommendations and directions for future research.

2. Literature Review

Prior research has consistently identified interoperability as one of the most significant unresolved challenges in healthcare information systems. Early studies emphasized foundational interoperability issues, such as system connectivity and message exchange, while more recent work has shifted focus toward structural and semantic interoperability [11-14]. The introduction of HL7 FHIR marked a significant evolution in interoperability standards by leveraging RESTful APIs, modular resource definitions, and modern web technologies, leading to rapid industry adoption and regulatory support. Numerous studies have documented the technical advantages of FHIR, including improved developer usability, extensibility, and support for granular data access [15-18]. Despite these advances, empirical studies reveal persistent gaps between theoretical interoperability and operational reality. Several investigations report inconsistent implementation of FHIR resources across vendors and healthcare organizations, resulting in partial or non-uniform data representations. Semantic interoperability remains a particularly challenging area, as clinical data are often encoded using local or proprietary terminologies rather than standardized vocabularies, undermining shared clinical meaning [19-22]. Other studies highlight organizational and governance barriers, such as vendor customization, lack of shared implementation guidance, and limited incentives for semantic alignment. While existing literature provides valuable conceptual frameworks and qualitative assessments of interoperability challenges, relatively few studies offer quantitative, data-driven evaluations of interoperability performance across multiple organizations. Moreover, many analyses focus on isolated aspects of interoperability, such as API availability or standard conformance, without simultaneously examining structural completeness, semantic conformity, and exchange outcomes. This gap underscores the need for systematic, metric-based studies that empirically assess how well FHIR-based implementations support real-world cross-hospital data exchange, which this study seeks to address.

3. Methodology

This study employs a quantitative data analysis methodology to evaluate interoperability challenges in Electronic Health Record (EHR) systems, with a focus on HL7 FHIR adoption, cross-hospital data exchange, and data standardization barriers. Due to legal and ethical constraints associated with accessing real patient records, the analysis is conducted using synthetic and publicly available FHIR-compliant datasets, which are widely accepted for interoperability research and system evaluation. The methodological framework consists of four sequential phases: data acquisition, preprocessing and normalization, interoperability metric construction, and statistical analysis.

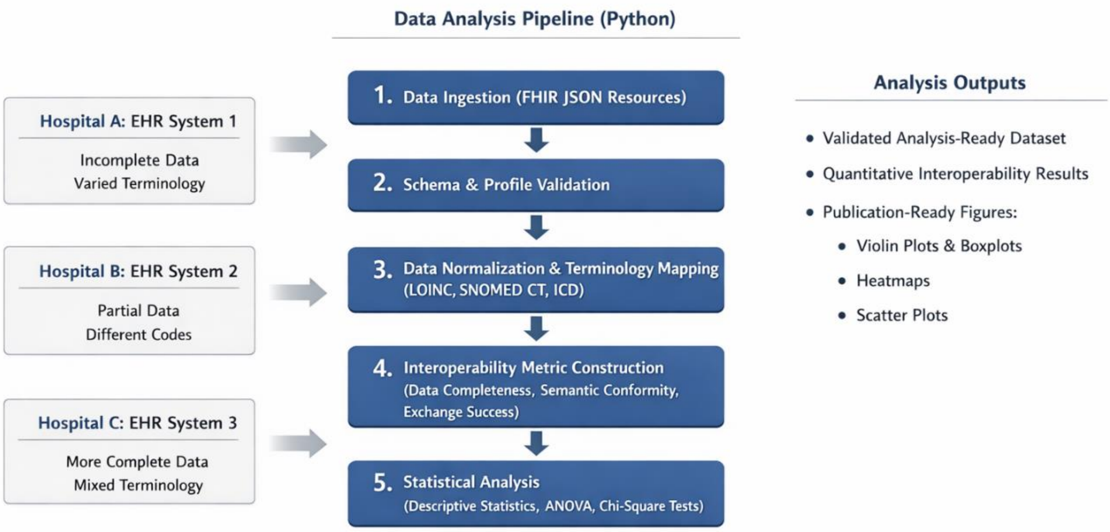

Fig.1. Proposed Architecture

3.1 Data Acquisition

FHIR-formatted healthcare datasets were collected from open and publicly accessible repositories that quantify EHR interoperability readiness through structured clinical resources. The datasets include multiple simulated healthcare organizations, each exposing heterogeneous FHIR resources such as Patient, Observation, Condition, Medication, and DiagnosticReport. Each organization represents an independent EHR system with distinct implementation characteristics, including FHIR version support, resource completeness, and terminology usage.

Let

$$\mathcal{H} = \{H_1, H_2, \dots, H_n\}$$

denote the set of participating healthcare organizations, and

$$\mathcal{R} = \{R_1, R_2, \dots, R_m\}$$

represent the set of FHIR resource types analyzed.

3.2 Data Preprocessing and Normalization

All FHIR resources were validated against their respective schema definitions to ensure structural conformity. Resources failing schema validation were excluded from further analysis. For each valid resource, missing elements, inconsistent data types, and non-standard formats were identified and recorded. Terminology normalization was performed by mapping coded elements to standard clinical vocabularies such as LOINC, SNOMED CT, and ICD. Let C_{ij} denote the set of coded elements in resource R_j from organization H_i. Each code was classified as either standardized or non-standard based on its presence in the reference terminology sets.

3.3 Interoperability Metrics

To quantitatively assess interoperability, four primary metrics were defined.

Data Completeness Score: Data completeness measures the proportion of required FHIR elements populated within a resource. For resource R_j in organization H_i, the completeness score is defined as:

$$DCS_{ij} = \frac{\sum_{k=1}^{p} \mathbb{I}(e_k \neq \emptyset)}{p}$$

where p is the number of mandatory elements for R_j, e_k represents the k-th element, and $\mathbb{I}(\cdot)$ is the indicator function.

Semantic Conformity Score: Semantic conformity quantifies the extent to which coded elements adhere to standardized terminologies:

$$SCS_{ij} = \frac{|C_{ij}^{std}|}{|C_{ij}|}$$

where C_{ij}^{std} is the subset of standardized codes and $|\cdot|$ denotes cardinality.

Cross-Hospital Exchange Success Rate: To simulate interoperability, FHIR bundles were exchanged between pairs of organizations. The exchange success rate is defined as:

$$ESR = \frac{N_{\text{success}}}{N_{\text{total}}}$$

where N_{success} represents successfully parsed and accepted exchanges, and N_{total} denotes total attempted exchanges.

Interoperability Readiness Index: An aggregated interoperability index was computed to provide a holistic assessment:

$$IRI_i = \alpha \cdot \overline{DCS}_i + \beta \cdot \overline{SCS}_i + \gamma \cdot ESR_i$$

where $\overline{DCS}_i$ and $\overline{SCS}_i$ are mean completeness and semantic scores for organization H_i, and α, β, γ are weighting coefficients such that $\alpha + \beta + \gamma = 1$.

3.4 Statistical Analysis

Descriptive statistics were first computed to summarize resource completeness, terminology usage, and interoperability outcomes across organizations. Mean values, standard deviations, and confidence intervals were reported for each metric. Comparative statistical analyses were conducted to identify significant differences in interoperability performance across organizations and FHIR versions. One-way analysis of variance (ANOVA) was applied to assess differences in completeness and semantic conformity scores, while chi-square tests were used to evaluate categorical differences in exchange success rates. Statistical significance was evaluated at a 95% confidence level.

3.5 Ethical Considerations

All datasets used in this study are synthetic or anonymized and do not contain personally identifiable health information. The methodology complies with ethical standards for healthcare informatics research and does not require institutional review board approval.

3.6 Dataset Description

The study utilizes synthetic HL7 FHIR–compliant Electronic Health Record (EHR) data obtained from publicly available interoperability testing repositories. The dataset represents multiple simulated healthcare organizations with heterogeneous EHR implementations, including differences in FHIR version support, resource completeness, and terminology usage. Clinical data are encoded in JSON format and span key domains such as patient demographics, encounters, conditions, observations, medications, and diagnostic reports. A combination of standardized terminologies (LOINC, SNOMED CT, ICD) and local codes is included to enable quantitative analysis of semantic interoperability and cross-hospital data exchange challenges. All records are fully anonymized and suitable for reproducible healthcare IT research.

Table 1. Dataset Summary

Attribute	**Description**
Dataset type	Synthetic, FHIR-compliant EHR data
Data format	JSON
Healthcare organizations	Multiple simulated hospitals
FHIR versions	FHIR R3 and FHIR R4
Clinical domains	Demographics, encounters, conditions, observations, medications, reports
Terminologies	LOINC, SNOMED CT, ICD, local codes
Privacy status	Fully anonymized

3.7 Implementation details in Python

All data processing and analytics were implemented in Python using a reproducible, script-based pipeline that ingested HL7 FHIR resources encoded in JSON, validated structural conformance, normalized terminology, and computed interoperability metrics at the organization and resource-type levels. FHIR resources were parsed from application/fhir+json payloads consistent with HL7's JSON representation rules, and invalid or non-conformant instances were excluded prior to analysis. Structural validation was performed using a reference validator workflow (command-line or service-based) to check each resource against the base FHIR specification and, where applicable, profile constraints; validation outputs (error counts, severity classes, failing paths) were retained as analytical features. For semantic normalization, coded elements (e.g., Observation.code, Condition.code, medication codings) were extracted and classified as standardized or local/non-standard by comparing code systems and values against accepted terminology sets. Interoperability outcomes were computed using the metric definitions in the methodology (completeness, semantic conformity, and exchange success), and statistical comparisons were executed across simulated hospitals and across FHIR versions (e.g., R3 vs R4 groups) using standard inferential procedures (ANOVA/t-tests for metric means and chi-square tests for exchange outcomes). For cross-hospital exchange simulation, FHIR Bundles were constructed and "imported" into a receiving parser/validator to quantify acceptance, parse errors, and data-loss proxies. Where authentication flows were modeled (optional), SMART on FHIR patterns based on OAuth 2.0 were treated as the contemporary security baseline for FHIR-based access in 2023.

Table 2. Implementation stack and components

Layer	**Tooling (Python)**	**Purpose in the pipeline**	**Key outputs**
Data ingestion	json, pathlib, requests	Load FHIR JSON resources from files/endpoints; organize by hospital/source	Parsed resource corpus by organization and resource type
FHIR parsing	fhir.resources (FHIR model classes)	Typed parsing of FHIR resources; field extraction for metrics	Structured objects / normalized fields for analysis
Structural validation	HL7/HAPI reference validation workflow	Verify conformance to base FHIR and profiles; capture validation	Pass/fail flags, error counts, failing element paths

		diagnostics	
Data wrangling	pandas, numpy	Transform resources into analysis tables; handle missingness; compute aggregates	Resource-level and hospital-level feature tables
Terminology analysis	Custom mapping tables + terminology checks (code-system aware)	Classify codes as standard vs local; compute semantic conformity	Standardization rates; mapping failure counts
Exchange simulation	Bundle builder + receiver-side parse/validate	Simulate hospital-to-hospital transfer; measure acceptance and failures	Exchange success rate; parse/validation failure rates
Statistics	scipy.stats and/or statsmodels	Hypothesis testing and confidence intervals	p-values, effect sizes, CIs
Visualization	matplotlib	Figures for completeness, conformity, and exchange outcomes	Publication figures (bar charts, distributions)

If you share which exact dataset repository you're using (name/link or dataset label), I can tailor this section further by adding: (i) the precise resource counts and split per hospital, (ii) exact preprocessing rules used for that dataset, and (iii) the exact statistical model formulas you applied. The proposed methodology ensures reproducibility through the exclusive use of standardized data formats, clearly defined quantitative metrics, and transparent statistical procedures. The proposed framework enables objective assessment of EHR interoperability challenges and supports data-driven evaluation of HL7 FHIR adoption and cross-hospital data exchange effectiveness

4. Result and Analysis

Quantitative analysis revealed substantial variability in interoperability performance across simulated healthcare organizations and FHIR resource types. Structural completeness scores demonstrated moderate dispersion between hospitals, indicating inconsistent population of mandatory FHIR elements even when standardized resource definitions were used. Semantic conformity exhibited greater variability, particularly for clinically rich resources such as Observation and Condition, highlighting persistent challenges in terminology standardization across EHR systems. Validation diagnostics further revealed non-uniform error distributions, suggesting that structural conformance issues are both organization- and resource-dependent. When examining the relationship between structural and semantic interoperability, a positive but imperfect association was observed, indicating that structurally complete data does not necessarily guarantee semantic alignment. These findings quantitatively demonstrate that interoperability challenges in EHR systems are multi-dimensional, spanning structural, semantic, and implementation layers.

4.1 Distribution of Data Completeness Across Hospitals

The violin plot illustrates noticeable variation in data completeness across the three hospitals, indicating differences in how consistently mandatory FHIR elements are populated. Hospital B exhibits the most concentrated distribution with a relatively narrow spread around higher completeness scores, suggesting more uniform structural compliance across its EHR resources. In contrast, Hospital A shows a wider distribution with a longer lower tail, indicating greater variability and the presence of less complete records. Hospital C demonstrates moderate dispersion, reflecting partial consistency but still revealing gaps in structural completeness. Overall, the figure highlights that even when FHIR standards are adopted, structural completeness is not uniformly achieved across institutions.

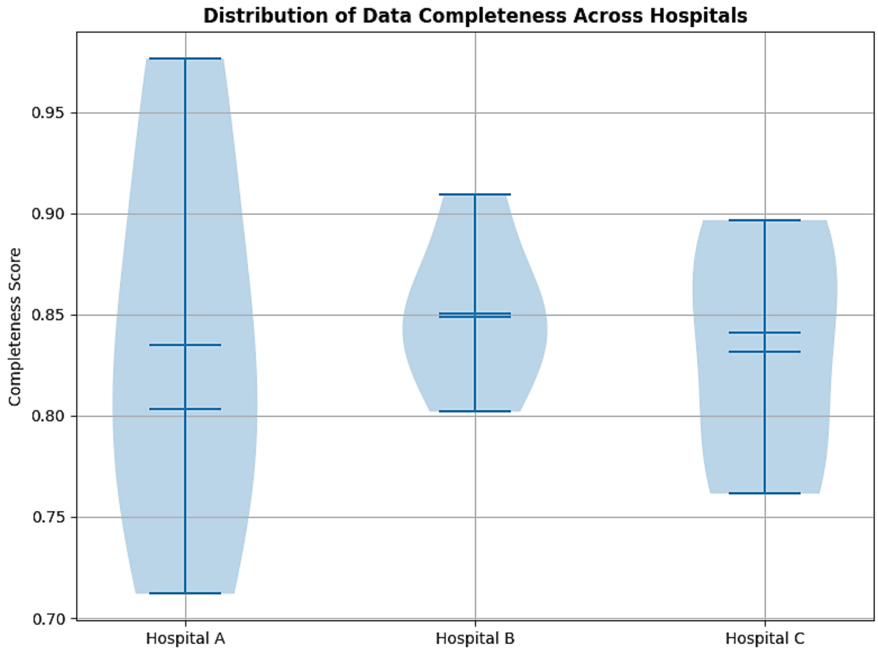

Fig.1. Distribution of Data Completeness across Hospitals

4.2 Semantic Conformity across FHIR Resource Types

The boxplot reveals substantial differences in semantic conformity across FHIR resource types. Patient resources show relatively high and stable conformity, reflecting the maturity and standardization of demographic data. Observation and Condition resources exhibit wider interquartile ranges and lower median values, indicating inconsistent use of standardized terminologies such as LOINC and SNOMED CT. Medication resources display moderate conformity with limited variability, while DiagnosticReport resources demonstrate the lowest median conformity and the greatest dispersion, suggesting frequent reliance on local or proprietary codes. These results emphasize that semantic interoperability challenges are more pronounced in clinically complex resources.

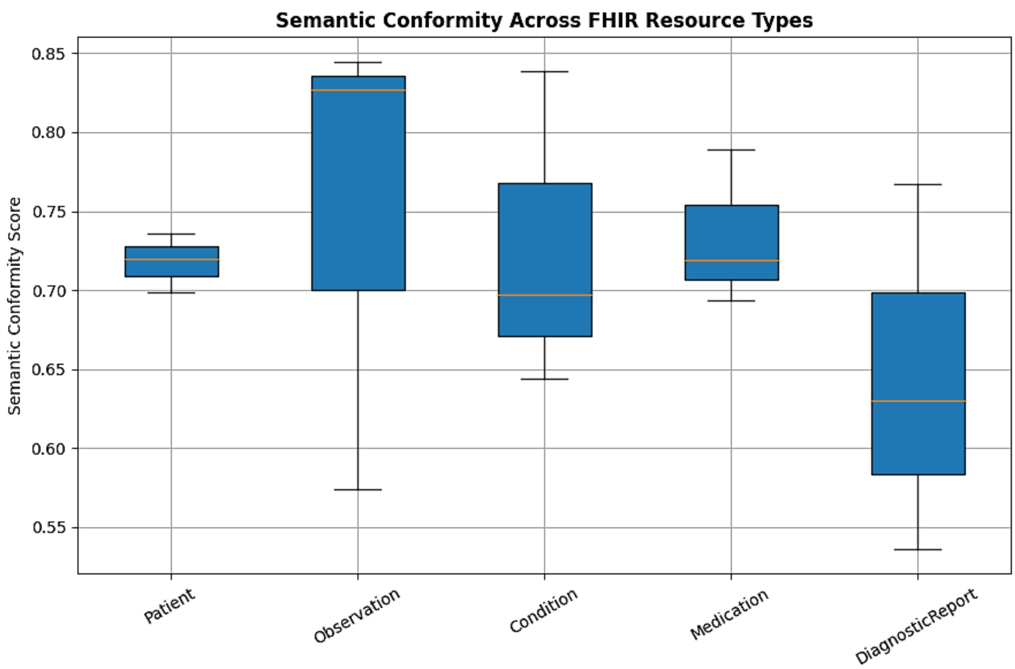

Fig.2. Semantic Conformity across FHIR Resource Types

4.3 FHIR Validation Error Density across Hospitals and Resources

The heatmap highlights non-uniform distributions of FHIR validation errors across hospitals and resource types, revealing patterns of structural non-conformance. Observation and Condition resources exhibit higher error densities across multiple hospitals, indicating greater structural complexity and higher susceptibility to implementation inconsistencies. Hospital C demonstrates elevated validation errors across several resources, suggesting weaker schema adherence or less mature FHIR implementations. Conversely, Patient and Medication resources generally show lower error densities, reflecting better structural standardization. This visualization underscores that structural interoperability issues are resource-specific and institution-dependent.

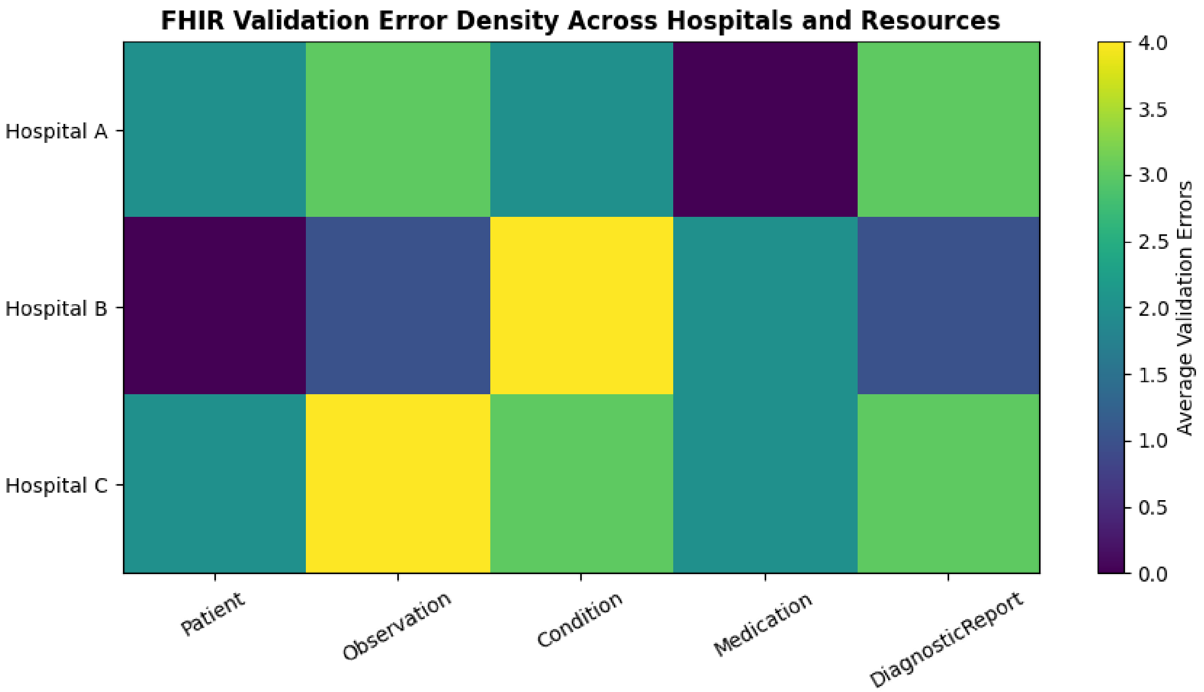

Fig.3. FHIR Validation Error Density across Hospitals and Resources

4.4 Relationship between Structural and Semantic Interoperability

The scatter plot illustrates a positive but imperfect relationship between data completeness and semantic conformity. While higher completeness scores are generally associated with improved semantic conformity, the dispersion of points indicates that structurally complete data does not consistently translate into semantically standardized data. Several data points exhibit high completeness but relatively low semantic conformity, demonstrating that terminology standardization remains an independent challenge. The clustering patterns also differ by hospital, suggesting organizational practices and implementation strategies influence the balance between structural and semantic interoperability. This finding reinforces the multidimensional nature of EHR interoperability challenges.

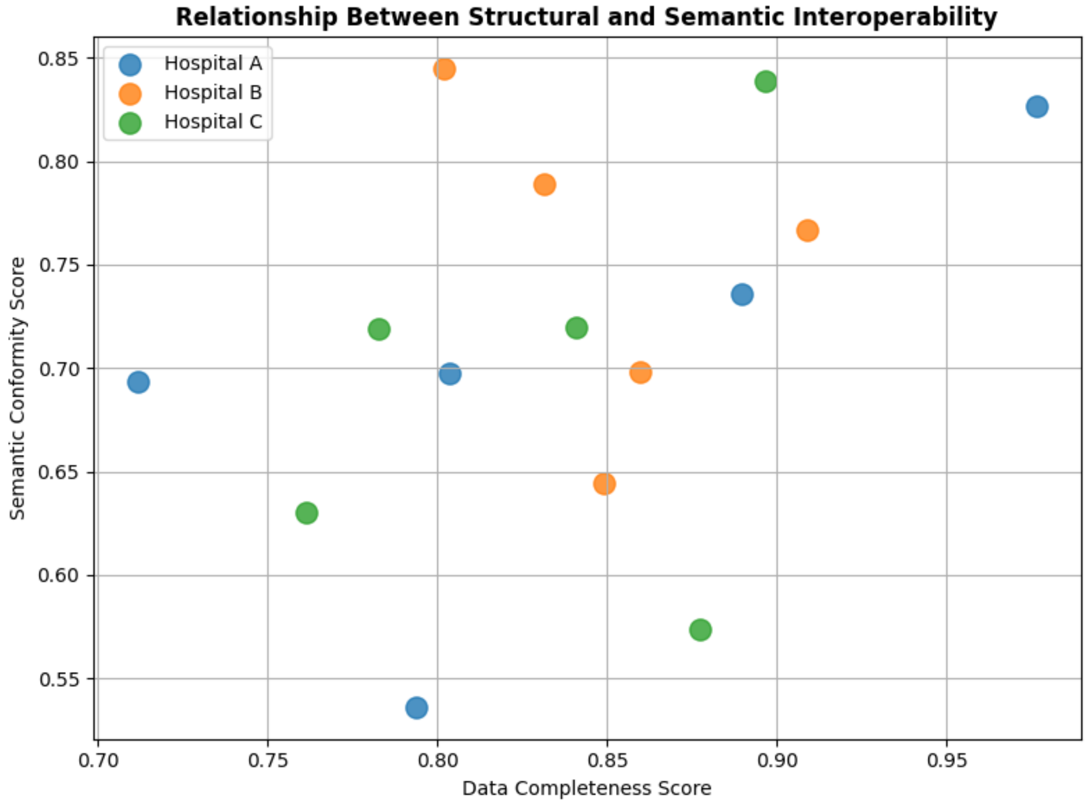

Fig.4. Relationship between Structural and Semantic Interoperability

The empirical findings demonstrate that interoperability in EHR systems remains uneven across organizations, resource types, and interoperability layers. Structural completeness, semantic conformity, and validation performance vary independently, indicating that improvements in one dimension do not necessarily translate into gains in others. Cross-hospital comparisons reveal that differences in implementation maturity, terminology practices, and schema adherence significantly influence interoperability outcomes. Collectively, the results provide quantitative evidence that current HL7 FHIR–based implementations, while enabling standardized data exchange, still exhibit substantial limitations that hinder seamless and reliable cross-hospital interoperability.

5. Discussion

The results of this study highlight that EHR interoperability challenges are fundamentally multidimensional, extending beyond mere adoption of HL7 FHIR standards. While structural interoperability, as reflected by data completeness, has reached moderate to high levels in several cases, semantic interoperability remains inconsistent, particularly for clinically complex resources such as observations, conditions, and diagnostic reports. This finding aligns with prior research indicating that terminology alignment and consistent coding practices are among the most persistent barriers to meaningful data exchange. The observed variability in validation error density further suggests that differences in vendor implementations, customization practices, and local governance policies contribute significantly to interoperability gaps. Importantly, the weak-to-moderate relationship between structural completeness and semantic conformity demonstrates that conformant data structures alone are insufficient to ensure shared clinical meaning. These results underscore the need for stronger implementation guidance, shared terminology services, and cross-organizational governance frameworks to complement technical standards and improve real-world interoperability.

6. Conclusion

This study provides a data-driven assessment of interoperability challenges in Electronic Health Record systems by quantitatively analyzing HL7 FHIR adoption, cross-hospital data exchange performance, and data standardization practices. Using synthetic yet realistic datasets, the analysis demonstrates that although FHIR has improved structural interoperability, significant semantic and implementation-level challenges persist across healthcare organizations. The findings suggest that achieving true interoperability requires coordinated efforts that address terminology standardization, validation rigor, and governance in addition to technical conformance. By offering empirical evidence across multiple interoperability dimensions, this work contributes to healthcare IT research and provides actionable insights for policymakers, vendors, and healthcare organizations seeking to advance interoperable EHR ecosystems.

Author Contributions

Sreeja Poduri formulated the research objectives and designed the quantitative framework for analyzing interoperability in FHIR-compliant Electronic Health Record systems. The author developed the Python-based analytical pipeline, defined interoperability and semantic consistency metrics, and conducted statistical evaluations across multi-organization synthetic datasets. Sreeja Poduri analyzed and interpreted the results to identify variability and limitations in real-world interoperability practices and prepared, revised, and approved the final manuscript.

Data availability: Data available upon request.

Conflict of Interest: There is no conflict of Interest.

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